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INFLUENCE OF POLITICAL EVENTS ON (PARTLY) STATE-OWNED COMPANIES: THE CASE OF EUROPE

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Abstract

The investigation of a sample of political events supports the thesis that state affiliated companies are less effected by uncertainty arising during political events. However, the occurring effect is only statistically provable when the consideration takes place on group level (partly state-owned vs not partly state-owned). The regression on company level does not prove robust to control variables. Moreover, the study indicates that sentiment retrieved from social media bears explanatory power for abnormal returns during political events. The level of sentiment, however, does not significantly influence the explanatory power of the state-owned variable.

Keywords
Finance, Event Study, Sentiment Analysis, Political Events, State-Owned Companies, Abnormal Returns

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1. Introduction

A large body of literature in finance is concerned with the connection between markets and politics. The field offers a variety of directions to investigate. Common areas include effects of historical or current political circumstances (e. g. parties in power), political connections and political uncertainty introduced by political events.

This work combines the latter two categories. The first part of the thesis analyzes the influence of political events on (partly) state-owned enterprises listed on a European stock exchange. Governmental holdings build a bridge between companies and the state. Within this framework, this work aims to investigate this political connection and to examine the effects on the respective companies. The research questions follow a logical strand. Does political uncertainty lead to abnormal returns? Are state-owned companies more susceptible to political risk triggered by political events? Or is the exact opposite the case, meaning that the connection protects companies from negative effects? Previous research investigates the aforementioned questions and theories mostly in emerging markets. Moreover, this research is often focused on country level. This work expands the research universe by considering political risk on European level with a focus on developed countries. Therefore, three influential events, namely the 2014 European Parliament election, the 2016 Brexit referendum and the 2019 European Parliament election, were chosen for the main sample. The second part of the thesis makes use of the globalized and interconnected world. Social networks make it possible to get reactions, opinions, and mood of people in real-time. This work aims to employ these real-time sentiments on political event research. This thesis examines the explanatory power of social media sentiment in context of abnormal effects during political events.

In the next chapter existing literature, related work, and theories in this area of research will be reviewed. Chapter 3 lays the methodological foundation for the data analysis and discussion in Chapter 4. The results are summarized in chapter 5.

2. Literature review and hypothesis development

2.1 Political uncertainty

The fundamental theory behind uncertainty in financial markets, established by Brown et. al. (1988), concludes that uncertainty inserts additional risk to the market. Risk aversion leads to a stock price set below the actual fundamental value. Once the uncertainty is resolved, abnormal positive returns occur. In accordance with the semi-strong EMH, an immediate adjustment is expected (Fama, 1970). The prevailing model, established by Pastor and Veronesi (2012), used to explain this theory in a political context, assumes falling stock prices as a consequence of increased political uncertainty. Pastor and Veronesi (2013) demonstrate that the drop in prices is initiated by a risk premium. The political risk premium compensates investors for increased volatility during time periods of political uncertainty. Increased volatility, triggered by political events, has been investigated and confirmed in various contexts (Bialkowski et. al, 2008; Bittlingmayer, 1998; Hillier & Loncan, 2019; Goodell & Vähämaa, 2013). Further convincing evidence is found by Kelly et al. (2016). The authors demonstrate, by observing planned political events, that political uncertainty is priced in option markets.

A common type of events used to research political uncertainty are elections (Bouoiyour & Selmi, 2017; Goodell & Vähämaa, 2013; Li and Born, 2006). An important contribution in this area is made by Pantzalis et. al. (2000). The work shows that the resolution of uncertainty may even happen prior to the election date. On the other hand, election outcomes do not necessarily resolve the uncertainty induced to the market. Positive upwards adjustments are then expected after the event date (Pantzalis et. al., 2000; Wong & Hooy, 2016). Other commonly investigated political events are war, terrorist attacks, coup d'états and political speeches (Wisniewski, 2016). A non-event-based approach is the investigation of political uncertainty through proxies. An example for that is the economic policy uncertainty index created by Baker et. al. (2016).

An example for closely related research in the European area is Hudson et. al (2020). Hudson et. al (2020) investigate the impact of Brexit events on a large number of British indices. Using GARCH models, the results indicate that risk and return on event days are largely in line with common asset pricing models and returns can be explained by the assigned risk premiums. Therefore, neither political uncertainty nor sentiment have an extraordinary impact on the financial indices' prices on event day. However, the results do not hold for several time windows around the event. Subsequently, Hudson et. al. (2020) check for abnormal returns. Similar, on the event days the cumulative average abnormal returns (CAARs) for most indices are insignificant, but in several time windows around the event abnormal returns are verifiable. Negative CAARs are especially evident for short windows following events classified as against the Brexit. Although a large part of the returns can be explained by traditional models, the outliers demonstrate that abnormal returns in this setting exist and hint on a sentiment effect.

In summary, theoretical models and evidential research suggests that political uncertainty influences stock returns. Wisniewski (2016), founded on a literature survey, expects this effect to be more prevalent in emerging countries due to the higher level of political instability. The large body of literature focusing on emerging countries is a possible consequence of this expectation. Furthermore, it could explain the comparably low evidence and research in the European area. Nevertheless, based on the findings in this chapter, the hypothesis is that abnormal returns are observable during political events (especially during elections).

2.2 Political events, political connectedness and state-ownership

This thesis examines the impact of political events on (partly) state-owned enterprises. In order to determine the consequences of political uncertainty on political connected firms, a definition by case is made. The first scenario assumes a risk reduction through political ties. Therefore, the political linkage protects firms during unsettling times, leading to higher prices relatively to private firms (Ashraf et. al, 2020; Boubakri et. al., 2012; Zhou, 2017). The second scenario views political uncertainty as threat to existing ties. Following this argumentation, political connected enterprises are more sensitive and suffer a stronger loss in price when the political situation is obscurer (Fisman, 2001; Hillier & Loncan, 2019; Liu et. al., 2017).

Liu et. al. (2017) find that the political risk theory, described in the previous chapter, holds true in China during the Bo scandal. Thus, during this time period of increased political uncertainty, falling stock prices are observable. Companies classified as politically sensitive experience a stronger drop. However, state-ownership is not equal to political sensitivity. Liu et. al. (2017) deliver an important academic contribution by showing evidence that the drop in price is a consequence of a higher discount rate and not due to lower expected future cashflows.

Ashraf et. al (2020) find that cumulative abnormal returns (CAAR) during political elections in Pakistan are less volatile for political connected firms. The results suggest that political connectedness leads to mitigation of political uncertainty arising from political events. The author affiliates the findings to investor sentiment. Thus, the trust of investors in the strength of the political connection, and accordingly the risk mitigation, will lead to less deviation from the mean. However, as in the previous paragraph, political connection needs to be differentiated from state-ownership. The requirements to be classified as political connected in the described work are easier to meet compared to this study. Zhou (2017) finds that the returns of state-owned enterprises in China during times of increased political uncertainty are not as heavily affected as the returns of private companies. However, both types of company have lower returns during these periods. Factoring in the different levels of state ownership, the author finds the effect to be mitigated the higher the share of state ownership is. By ruling out global risk factors through further analysis, the author concludes that less exposure to political risk as a consequence of the political ties are the best explanation for this finding.

Wong and Hooy (2016) investigate the impact of elections on state-owned and non-state-owned banks in three countries in South East Asia. The authors find, while both types of banks have positive CAARs over the event windows, that the positive effects are stronger for governmental banks. Further, the result supports the uncertain information hypothesis of Brown et. al. (1988), which assumes passive behavior of investors during times of uncertainty, followed by increased returns after the resolution of the uncertainty. Other studies finding positive effects for politically linked companies are Chen et. al (2013) and Lin et. al. (2016).

On the other hand, Hillier & Loncan (2019) observe an external political shock in Brazil in 2017 and its impact on stock returns. The results support the view that political linked companies (along with cross-listed companies) belong to the stronger affected group in the context of political uncertainty. Furthermore, the results indicate that political connectedness is one of the main drivers to transfer political risk to stock markets.

Based on the aforementioned literature, a clear hypothesis whether state-owned companies are stronger or less affected can not be made. However, based on the literature in this section, the hypothesis is made that differences between both groups in terms of abnormal returns exist.

2.3 Sentiment and Twitter

Twitter is a social media platform that allows users to express opinions and to share information in real-time short-text messages. The chance to extract public sentiment from these tweets has attracted many schoolers to revolve their academic research around this platform. Nisar and Yeung (2018) investigate the correlation between public mood expressed in tweets and FTSE movements. Despite a lack of statistical significance, the authors conclude that the results suggest a causal relationship between these variables. The work dedicates the missing significance could be an implication of the small window of observation.

Furthermore, the predictive power of public mood is investigated in several papers. Nisar and Yeung (2018) find no statistical relevant predictive power when investigating the FTSE. On the other hand, Bartov et. al. (2018) show that predictive ability exists in aggregated twitter opinion during earnings season, while Bollen et. al. (2011) come to the same result when investigating Dow Jones prices. Another important finding by Bartov et. al (2018) is that the results are valid regardless of the originality of information included in the tweet. Combined with the robustness when correcting for traditional media opinion and the evidence that the effect is even stronger for companies with less coverage, the results demonstrate that Twitter data is helpful in determining stock prices. Mao et. al. (2012) find a positive relation between volume of tweets and closing prices. On the other hand, Nisar and Yeung (2018) cannot confirm this relation for the British stock exchange FTSE.

This work uses sentiment to classify event days. That the classification of events can help to explain abnormal returns is shown in Dangol (2008). The work provided evidence that, depending on the direction of the political news (positive or negative), a corresponding adjustment and thus abnormal returns follow. Furthermore, this work aims to test the positive predictive ability of sentiment, found by Bartov et. al. (2018), in an event setting.

3. Data Sampling & Methodologies

3.1 Data Sampling

The scope of investigation ranges from 2010 to 2019. The constituents of the STOXX Europe 600 as of 01.01.2010 were chosen as sample. The index was chosen because it provides a cross section through all company sizes throughout the European stock market. Moreover, the index focuses on developed countries, which allows for a more isolated investigation of the impact major events on developed countries as opposed to developing countries in prior research. Furthermore, the index delivers a readily available group of over 50 state-owned companies (in context of the definition within this work). The historical date was chosen to eliminate most of the survivorship bias. It must be mentioned that a minor part remains due to lack of information on delisted stocks. The data was retrieved from Thomson Reuters Eikon. The classification as partly state-owned company (for facilitated readability described as SOE or state-owned companies in the following sections) is made when the state stake exceeded 20%. All stakes from European state-owned entities (including sovereign wealth funds and local governments) were considered. The ownership classification followed a two-step process. Firstly, the holdings data provided by Eikon was analyzed. However, due to sporadically inconsistent data (e. g. in classifying state-owned entities) and missing data, manual adjustments were conducted. Data was verified or falsified by annual reports, company websites and Bureau van Dijk's Orbis. The 20% threshold was chosen based on the definition of minor state-owned company by the European Commission (2016). Partly state-owned companies and state-owned companies (over 50% ownership stake) were bundled into one group to maintain at least thirty state-owned companies in each specification.

The event selection orientated on prior research (Kaplanski and Levy, 2010; Hudson et. al., 2020). The main sample has the goal to observe expected events with uncertain outcome that have major supranational impact. Following the literature part, especially elections fall under this definition. The European Parliament elections are a stereotype for such an event since the result of the election impacts all future supranational policies and decisions for the next five years. The EU referendum of Britain, on the other hand, majorly impacts the supranational level by potentially removing the fourth biggest parliament member and therefore, a significant voter and decision maker from the EU. The sub-samples investigate different types of events. The first sub-sample investigates internal regulations, while the second sub-sample investigates events related to crises. The event selection process for the sub-samples was done by collecting and classifying listed events from the official homepage of the European Union (European Commission, 2021).

The extraction of historical tweets posed a difficulty due limited availability of datasets. For the EU referendum event, the dataset of North et. al (2020) was used. This dataset allowed to analyze sentiment based on over 70.000 tweets during the event window.

3.2 Methodology 1: Cumulative Average Abnormal Returns (CAAR)

The event study method (Fama et. al, 1969) is used to investigate the impact of political events on the sample. The method enables an investigation of daily effects, the individual effects of a single event as well as of all events as a whole by the delimitation of the individual process steps. The first step involves calculating daily abnormal returns (AR) for each constituent of the sample during the event window of a single event. The day of the event is defined as t=0. Additionally, the ten days before and after the event are considered in the analysis. Day 10 before the event is defined as t=-10 and day 10 after the event as t=10. All days in between are defined according to this scheme. In order to calculate ARs, expected returns of the companies need to be estimated. In theory, any model can be used for this purpose (among others the capital asset pricing model, market model, mean-adjusted returns). Keeping in line with previous studies in this area (Ashraf et. al., 2020; Dangol, 2008; Hudson et. al 2020; Janssen, 2014; Liu et. al., 2017; Repousis, 2016; Wong and Hooy, 2016), the market model is used.[1] The model has the following specifications (MacKinlay, 1997):

$$R_{i,t} = \alpha_i + \beta_i \times R_{M,t} + \varepsilon_{i,t} \qquad \textit{Eq. 1}$$

where $R_{i,t}$ is the return of stock i at time t; α_i is the intercept of stock i; β_i is the sensitivity of stock i to the market; $R_{M,t}$ is the market return at time t; $\varepsilon_{i,t}$ is the error term; $E(\varepsilon_{i,t}) = 0$; and $var(\varepsilon_{i,t}) = \sigma_\varepsilon^2$. The expected return $E(R_{i,t})$ is then calculated as follows:

$$E(R_{i,t}) = \alpha_i + \beta_i \times R_{M,t} \qquad \textit{Eq. 2}$$

The parameters α_i and β_i are estimated over a time period not affected by the event. The estimation window in this case will be determined from trading day -110 up until trading day -11 before the event. Finally, the ARs are calculated as:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \qquad \textit{Eq. 3}$$

where $AR_{i,t}$ is the abnormal return of stock i at time t; and $R_{i,t}$ is the realized return of stock i at time t. The second step involves the calculation of average abnormal returns (AARs) on a

[1] Hudson et al. (2020) use both, the mean-adjusted and the market model. The results are consistent for both models. Liu et. al. (2017) use both, the market adjusted return and market model. The results are consistent for both models.

daily basis. The previous calculated ARs of each stock will be summed and divided by the total amount of stocks. The following formula will be applied:

$$AAR_t = \frac{1}{N} \times \sum_{i=1}^{N} AR_{i,t} \qquad Eq.\ 4$$

Where AAR_t are the average abnormal returns at time t; and N is the number of stocks in the sample. In order to measure the effect for the whole event over the complete sample, the AARs will be added. The cumulative averaged abnormal returns (CAARs) are expressed by the following formula:

$$CAAR = \sum_{t=T_1}^{T_2} AAR_t \qquad Eq.\ 5$$

Where T_1 is the beginning of the event window and T_2 represents the end of the window. The null hypothesis is:

$$H_0: CAAR = 0 \qquad Eq.\ 6$$

Following Brown and Warner (1985) the cross sectional t-test is applicable:

$$t(CAAR) = \sqrt{N}\frac{CAAR}{\sigma_{CAAR}} \qquad Eq.\ 7$$

$$\sigma_{CAAR}^2 = \frac{1}{N-1}\sum_{i=1}^{N}(CAR_i - CAAR)^2 \qquad Eq.\ 8$$

Where CAR_i is the cumulative abnormal return of stock i over the whole event window and σ_{CAAR} the standard deviation of the cumulative average abnormal returns. The event studies are conducted with the research apps of Schimmer et. al. (2014).

In order to confirm the effect of state ownership on company level, a regression with control variables will be conducted (similar to Wong & Hooy,2016). The independent variable are the CARs over the event window. The following model is estimated:

$$CAR = \alpha + \beta_1 SOE + \beta_2 SIZE + \beta_3 LEVERAGE + \beta_4 GROWTH + \varepsilon \qquad Eq.\ 9$$

Where SOE is a dummy variable for state-ownership; $SIZE$ is the market capitalization of the companies; $LEVERAGE$ the debt/equity ratio and $GROWTH$ the sales growth.

Additional robustness tests use different test statistics and abnormal return models.

3.3 Methodology 2: Sentiment Analysis

The methodology in this section is derived from research mentioned in 2.3 (Bartov et. al, 2018; Nisar and Yeung, 2018). The individual determination of sentiment is done by using a lexicon-based approach. According to that, every single element of a tweet will be compared to predetermined words, classified as either positive or negative. A threefold division follows, classifying a tweet as 'positive', 'negative', or 'neutral'. In order to aggregate the sentiment of all tweets, a variable named TEMPER is defined:

$$TEMPER_t = \frac{(positive\ tweets_t - negative\ tweets_t)}{total\ tweets_t} \qquad Eq.\ 10$$

The variable expresses sentiment in a numeric term between 1 and -1. Values close to zero indicate neutral sentiment, whereas values closer to 1 or -1 indicate strong positive or strong negative sentiment, respectively. This method is sensitive to the staring inputs, namely the lexicon words, because no machine learning tool is implemented. The sentiment classification is done by using the natural language toolkit in Python. The opinion lexicon by Hu and Liu (2004) is used for this purpose. TEMPER will be used twofold. Firstly, as an interaction term with SOE in the above mentioned equation (Eq. 9). Secondly, as predictor for the abnormal returns after the events. This is estimated in the following two models:

$$AR_t = \alpha + \beta_1 TEMPER + \beta_2 TEMPERxSOE + \beta CONTROLS \qquad Eq.\ 11$$

$$AR_t = \alpha + \beta_1 TEMPER_{t-1} + \beta_2 TEMPER_{t-1}xSOE + \beta CONTROLS \qquad Eq.\ 12$$

4. Discussion of the topic

4.1 Empirical findings for the major event sample

The first table[2] shows the AARs for the days within the event window of the three major events and Table 2 the CAARs for the corresponding windows.

In the long window both groups of companies have a negative CAAR. However, only the CAAR of the non-SOE group shows statistical significance ($p<0.001$). Moreover, in the medium window the results for SOEs and non-SOEs diverge stronger. While SOEs have a non-significant positive CAAR of 0.56%, non-SOEs post a CAAR of -0.41% at 5% significance level. The short window results in positive CAARs for both groups. Again, a similar observation is made. The positive CAAR of 0.35% for non-SOE is significant at 1% level, while the positive CAAR of 0.56% for SOEs is not statistically significant. Summarizing, no significant impact on state-owned companies can be found in two out of three analyzed windows. All windows are significant for non-SOE companies.

In the long window, 11 AARs are significant at the 0.1% level for non-SOE companies. Out of this 11 AARs, only three are positive. It is interesting to note that out of these 11 AARs, seven are found before the event and three afterwards. The remaining significant AAR is on

[2] All tables are placed in the appendix.

the day of the event itself and positive. The highest negative result is found 7 trading days before the event, while the highest positive day is 4 trading days before the event. Another observation is that the days furthest away from the event (-9, -10,10,9) do not produce significant results at the 1% level. As expected after the evaluation of the CAARs, the number of significant AARs is substantially lower for state-owned enterprises. The four significant days can be found on Trading Day -8, -7, -2 and 0 (at 99% confidence level). More precisely, this means that no significant AARs for this confidence level can be found for SOE after the event. Solely the AAR on event day is positive. The strongest negative impact is as with the non-SOE companies also on day -7.

The results so far indicate a tendency that non-SOE companies are more sensitive to political events than the state-owned enterprises. The significant negative returns over the medium and long window for non-SOE companies are a supportive example for the negative effect of political induced uncertainty as modeled by Pastor & Veronesi (2013). On the other hand, the mean of the state-owned enterprises does not significantly deviate from zero. Looking back at the two opposing theories regarding state-owned companies during political uncertainty, the results so far support the findings of the risk reducing theory (Ashraf et. al, 2020; Boubakri et. al., 2012; Zhou, 2017). Accordingly, political connections protect against political uncertainty, and this risk-reducing factor is reflected in this sample by non-significant deviations during political event periods. This is especially evident in the medium window and long window. Closely around the event (short window), the resolution of uncertainty is observable, which leads to a positive AAR for the non-SOE group.

Other parametric tests were used in order to verify the findings. The Patell Z (Patell, 1976), adjusted Patell Z (Kolari & Pynönnen, 2010) and BMP test (Boehmer et. al.,1991) were used for this purpose. The Patell Z adjust standard errors of the ARs and standardizes them. The test corrects for a violation of the identic distribution assumption. Adjusted Patell Z additionally corrects for cross correlation. The BMP test corrects for volatility triggered by the event. The tests are found in table 3&4. The use of other test statistics does not alter the findings for the large window described above. However, the CAAR of the non-SOE group loses its statistical relevance in the medium window. Moreover, the CAAR of non-SOE in the short window loses its significance when applying the adjusted Patell Z. This suggests that cross correlation has created a bias. Concluding, the result and explanation from the previous paragraph hold true for the large window.

The next paragraphs discuss effects on single event level. A comparison between all models is found in table 5. Results for the European Election 2014 are in tables 6-8; results for Brexit 2016 in tables 9-11; and results for the European Election 2019 in tables 12-14. Analyzing the CAARs around the European Parliament election 2014 leads to significant results at the 0.1% significance level for the medium and short time window. Both CAARs are positive (0.0154 and 0.007, respectively). Nevertheless, no significance can be evidenced for the long window. In this case, it is noticeable that the company type is not as decisive as on the bundled event level. In other words, over the short window both CAARs are positive and significant at minimum 99% confidence level. Over the middle window, both CAARs are also significantly positive, but the returns of the SOEs only at 5% level. The CAARs over these periods are higher for the SOE group (0.0201 and 0.0114, respectively) than for the non-SOE group (0.0149 and 0.0066, respectively).

The referendum vote produced negative CAARs for the long and medium window at 0.1% significance level (-0.0352 and -0.0221, respectively), but no significant CAAR for the short observation window. In terms of company type, the CAARs behave closer to the overall sample than to the European Parliament election 2014. This is especially true for the long window, in which a highly significant negative CAAR for non-SOE (0.1% level) can be found. For SOEs the CAAR is not significant at all in the same window. A different situation is observable for the medium window. Both CAARs are significantly negative (99.9% confidence level for non-SOE, 95% for SOEs).

The third event, the European parliament election in 2019, shows a different pattern compared to the other two events. Over the short time window, a negative CAAR at 1% significance level occurs. The mathematical sign is reversed over the long window, leading to a negative CAAR at 5% significance level. Lastly, the medium window shows no statistical significance. CAARs on company type level behave similar to the overall sample again. Over the long window, non-SOE have a significant negative CAAR (at 1% level). The same is true for the medium window, although only at a 95% confidence standard. All CAARs for the SOE group are positive, however, none is statistically significant.

Eleven highly significant days (1%-level) are observed during the European Parliament election 2014. Most of them, namely 7 of the 11, are found before the event. Additionally, one more AAR appears before the event if the significance level is changed to 5%. The event day itself is highly significant, followed by statistically significant abnormal average returns on day +1, +4 and +8 (at 1% significance level). After the event one additional significant AAR (day +6) can be found when changing the significance level. In terms of sign, the first set of significant days (-9, -8, -7, -6) are negative with values ranging from -0.0015 to -0.0075 (1% significance level). The sign flips for the next set of relevant days (-5, -2, -1). The returns, however, show weaker magnitude (ranging from +0.0017 to +0.0028). The sign remains positive at the event day and on the following significant days (ranging from 0.0037 at the event day itself to 0.0017). In accordance with the whole sample, the amount of AARs of non-SOE companies exceeds the amount of AARs of SOEs. The non-SOE have significant AARs on 11 out of 21 days, whereas the SOE sample only has AARs on 4 days (significance level: 1%). Concluding, the insignificance of the large window is driven by the quick adjustment around the event.

During the Brexit referendum eleven highly significant days (1%-level) are observed. The AARs are equally split relative to the event day. Changing the significance level yields one more significant day after the event (day +4). Prior to the event, four of the five AARs are negative, reaching from -0.0025 to -0.0088. The event day itself has a positive effect (+0.0021), followed by a negative AAR on day +2 (-0.0116). Then two positive AARs follow on days +5 and +6. The last two AARs on day +7 and day +8 are negative again. A possible explanation for this diverging observation compared to the first event is that the uncertainty is not resolved after the event day. On the contrary, the Brexit is an unprecedented event in the history of the EU and thus, the majority voting leave introduces even more political uncertainty. Still finding a high density of abnormal average returns after some days have passed as well as them being bidirectional explains the significance of the large window and simultaneously the irrelevance of the short window.

Lastly, during the observed 21 days in context of the European Parliament election 2019, eight highly significant AARs (1%-level) are found. Out of these 8 AARs, six are observed before the event, whereas two are observed after the event. The event date itself is only significant at 5%-level. Furthermore, three additional AAR are observed at the 5%-level. Prior to the event, four out of five AARs are negative. The negative values range from -0.0028 to -0.0051. The event date itself yields a positive AAR of 0.0024, followed by two further significant positive AARs of 0.0018 (day +1) and 0.0024 (day +6) at 5% significance level. After a sign flip on day +8, resulting in a negative AAR of -0.0017, two positives significant AARs follow (5% significance level). With one exception in each case, AARs before the event can be classified as negative and AARs after the event as positive. This aligns with the standard theory of political uncertainty described in chapter 2 (Brown et. al.,1988; Pantzalis et. al.,2000). Before an event uncertainty arises, which leads to negative abnormal returns. After the event, the uncertainty is resolved, and abnormal positive returns occur. It is unusual, however, that after the initial adjustment (day 0 and day +1) further adjustments occur only after a certain time. A possible reason for this distribution is that closely after the event not all uncertainty is resolved. A straight-forward explanation is that new alliances have to be formed. Theoretically that is also the case for the European Parliament election 2014. However, vote distribution deviates stronger from 2014 to 2019 than from 2009 to 2014. In this context, the negative CAAR over the long window indicates that there is remaining uncertainty or simply that the event had a negative abnormal effect on the market.

The analysis on event level leads to two main statements. Firstly, all events have statistical relevance and thus the results are not driven by an outlier event. Secondly, the individual analysis demonstrates how differently the market reaction behaves. In this sample alone three different scenarios are observed. The first scenario is a quick adaption around the event date (EP2014). The second scenario depicts a longer lasting adaption period (EP2019), while the last scenario leads to a non-resolution after the event, which is equivalent to the creation of additional uncertainty in theory. Furthermore, the first event shows characteristics of another scenario, the scenario of a (partial) resolution of uncertainty prior to the event. Beyond that, the events demonstrate that it is difficult to establish predictions prior to the event window on how CAARs and AARs behave when one is solely considering the event type.

4.1.2 Empirical findings for the sub sample

This section investigates other types of political events in order to observe similarities and differences compared to the main sample. This section is intended to provide a starting point for further research in this area. Table 15 depicts the chosen events; tables 16-17 the results for the first sub-sample and tables 18-19 for the second sub-sample.

The first sub-sample bundles four parliamentary votes on regulations and trade agreements. The sample aims to control whether the effects of the main sample hold for non-major events. The sign of the CAAR over the long window is positive (0.0019), but not significant. Significant AARs are mainly found after the event. However, in contrast to the main sample, no clear pattern is observable in terms of positive or negative impact since signs are changing almost daily. Therefore, the typical negative movement followed by positive abnormal returns cannot be determined in this sample. Differentiating between SOE and non-SOEs yields only one significant return. The CAAR of the non-SOE group is -0.0036 at 95% confidence level. In this context, the SOE are less affected again. A straightforward explanation for the insignificance is the smaller relevance of the event sample. While the main sample captures effects on the parliament itself, the votes capture the actions of the parliament. On the other hand, the significant AARs which are concentrated after the event indicate a relevance of the events, especially for non-SOEs. The difference to the main sample is a relatively calm pre-event period, which leads to the insignificance of the windows.

The second sub-sample bundles three non-announced events related to major crises in Europe during the 2010s. In order to isolate the effect of the events, only the post-event days were investigated. More concretely the events are not the beginning of the crisis, but rather larger events within the crisis period. In order to avoid negative effects triggered by the crisis itself, only the post-event dates are analyzed. There are no significant CAARs for the long and medium window ([0,10] and [0,5]). However, both short-term windows ([0,1] and [0,2]) yield significant negative CAARs for the non-SOE group (at 99.9% confidence level). On the other hand, no statistical evidence for a cumulative average abnormal return different than zero is observable when investigating the SOE group. Concluding, the same behavior as in the main sample is observable. The theory mentioned in the previous chapter holds for this sample of political events, despite different characteristics.

4.2 Robustness Checks

4.2.1 Sensitivity to the underlying model

The market-model is a commonly used model in event study methodology (see for comparison chapter 3.2). However, in order to confirm that the results are not sensitive to the underlying model, the calculations were repeated with the market-adjusted model and mean-adjusted model. The first model equals the expected return of a stock with the market return, whereas the second model equals the expected return of the stock with the mean return of the stock in the estimation period (MacKinlay, 1997). Even though the models are more naïve in their basic specification, they are suitable as supplements due to their slightly different definition of abnormal returns. Table 20 depicts a comparison across models; tables 21-22 the results for the market-adjusted model and tables 23-24 for the mean-adjusted model.

The market-adjusted model yields a negative CAAR of -0.0132 over the whole sample, which is significant at the highest level (0.01%). For comparison, the CAAR of the market model was -0.0146 and also highly significant. In terms of company type, a similar picture as in the first model is painted. Over the long window only the CAAR of the non-SOE (-0.0142) is highly significant (0.1% level), whereas the CAAR of the SOE is not significant at any of the general accepted confidence levels. The medium window results behave like in the previous model. This is, a significant negative CAAR for the non-SOE group (-0.0044 at 5% level) and an insignificant positive CAAR for the SOE group. Moreover, the same observation as for the market model in regard to the short window can be made. Both CAARs are positive, while only the non-SOE CAAR is statistically significant (at 0.1% level). On 12 of 21 days highly significant AARs are observable for non-SOE (market model: 11/21) and 3 of 21 highly significant AARs for SOEs (market model: 4/21) at 99% confidence level. Results overall are fairly similar, despite deviating sparsely in magnitude. More importantly, the model in no way calls into question the previous results. On the contrary, the same tendency for higher sensitivity of non-SOE to political events is prevalent.

The statements that can be made when using the mean-adjusted model are largely the same as with the previous models. However, the results are more negative, leading to differences in sign and significance level in some cases. That the overall pattern is the same can be seen, for example, when viewing the CAAR over the whole sample. Here the direction of the sign and the significance level are the same, but the CAAR is vastly negative with a value of -0.0366. The same is true for the medium window, in which the CAAR of SOE is insignificant positive. However, the negative CAAR of non-SOE (-0.0078) is now significant at a 1% level in the [-5;5] period. On the other hand, using the mean-adjusted model leads to a significant CAAR of SOEs in the large window (at 5% level). The CAAR for non-SOE stays significantly negative (at 0.01% level). A drastic change is observed in the short window. The sign changes for both CAARs. The CAAR of the non-SOE group in the short window is now significant negative instead of significant positive. The CAAR of the SOE group remains insignificant. The same effect is visible when analyzing AARs. Thus, 19/21 days are highly significant (0.1% level) for non-SOE and 14/21 for SOEs. Although the results are not aligning perfectly, the overall tendency of more sensitivity of non-SOEs is even more prevalent in this model.

On closer inspection, it is rationally explainable why the mean-adjusted model deviates stronger from the market model than the market adjusted model. The latter models implement market risk in their specification (one through betas and the other one by equaling it to the expected return). This statement is imprecise for the mean-adjusted model. One could argue that the model indirectly incorporates historical market risk factors by using the average stock performance over a longer estimation period. However, as Klein and Rosenfield (1987) state, the residuals will be biased when the observing period is bullish or bearish.

4.2.2 Regression Analysis

In order to validate the results found in 4.1, regression analysis with control variables was carried out for the event windows. Therefore, three models were used. The OLS model, the firm fixed effects model and random effects model. Moreover, the regressions were carried out with- and without time fixed effects. The OLS model is rather naïve, since it assumes that CARs are not affected by company individual effects. The firm-fixed model is not well specified for this sample since the main explanatory variable (SOE) is not fixed for all companies over all periods. Moreover, Hausman tests demonstrated that random effects are a better fit for all of the following regressions compared to fixed effects. Thus, analysis focuses on OLS and random effects.

The results for the large window can be found in table 25-28. The beta of the dummy variable SOE (1 if SOE,0 if non-SOE) is positive in all specifications. However, the coefficient is not significant in neither the OLS nor in the random effects model. By contrast, the coefficient of the control variable SIZE is significantly positive in both models. The other two coefficients of growth and leverage do not have any statistical significance for the dependent variable CAR. This is true for all models. Since this result was not expected based on previous investigations, the regression was repeated with a higher level of state-ownership (30%). The justification for this is based on Zhou (2017). The author shows that negative effects introduced by events shrink with a higher level of state-ownership. In context of the work at hand, the result does not change drastically. The regressions can be found in table 29-32. The SOE coefficient is significant positive at 5% level in the first OLS regression, however, after controlling for other variables, the significance vanishes. On the other hand, as in the previous regression, the company size shows significance at the highest degree. The random effects model yields a p-value of 0.052 for the SOE coefficient. Thus, the null is accepted. As in the OLS model, size is highly significant in all specifications.

In a third regression (tables 33-36), the state-owned companies not listed on a stock exchange in an EU country were removed (in this case Norway and Switzerland). The purpose of this regression is to investigate whether the EEA agreement signing countries not belonging to the EU distort the results. As in the first set of regressions, no statistical significance is found for the SOE coefficient in the OLS model and random effect model. This result was expected due to the removal of companies with state-ownership over 30%, while keeping some lower percentages in the sample.

4.3 Sentiment Analysis

A further point of observation is the impact of sentiment. In this section, the focus point will shift from a window observation to daily observations. The goal is to classify days in the event window as either negative or positive (table 37). Following that, the error terms (ARs) will be regressed against the TEMPER variable and the SOE variable in interaction with the TEMPER variable. In a third step, the variable will be lagged in order to observe the predictability of ARs based on TEMPER. The analysis was only done for the Brexit event. There are two reasons for that. Firstly, the event period is the most consistent in terms of synchronous trading of the sample companies. Secondly, a public dataset of historical tweets was only obtainable for the EU referendum. Thus, the analysis is limited to this event only. Nevertheless, the high number of observations allow for a good informative value. The OLS was used because control variables per firm are not changing. Time fixed effects were disregarded since only a 21 day period is observed.

The first set of regressions (table 38) clearly shows that the continuous variable TEMPER has a significant impact at 99.9% confidence level. The coefficient is positive. Thus, the relationship is as expected. Positive aggregated mood positively impacts abnormal returns, while negative aggregated mood leads to the opposite. The statement and statistical evidence remain unchanged when adding the control variables. As in the previous chapter, the only statistically significant coefficient of a control variable is beta2 with 99.9% confidence.

The second set of regressions (table 39) depicts the interaction between SOE and TEMPER. The TEMPER coefficient is statistically significant. Thus, the slope for the non-SOE group is positive. The interaction term yields no statistical relevance. This can be interpretated as no statistical difference between the slopes of SOEs and non-SOEs in dependence of mood on the respective day. The third set of regressions treats TEMPER as a binary variable. TEMPER on a given day in this scenario is either good (=1) or bad (=0). The results are portrayed in table 40. The statistical relevance is lower than before, however, the interpretation does not change. In conclusion, both groups of companies behave similar in both states of the world. No statistically different slope is detected, neither when observing the level of TEMPER (second set of regressions) nor when observing the two states of the world (third set of regressions). The last set of regressions (table 41-42) shows that the significance holds, although only at a confidence level 99%, when using the one day lagged TEMPER variable. Interestingly, the sign of the coefficient switches. Therefore, a positive TEMPER on the previous day on average lowers the AR on the next day. Furthermore, the p-value of the interaction term shrinks close to the 5% threshold (p-value: 0.051, t-value: 1.95). The coefficient is positive.

The results deliver evidence to negate the risk reduction theory in this setting due to the fact that the coefficient of the interaction term is not significant in any of the models. Thus, it cannot be concluded that the significance of the SOE variable is dependent on the level of sentiment on a given day. The hypothesis that the SOE variable shows relevance on extreme days is rejected. Despite not meeting the required level to be labelled significant, the last set of regressions indicates that an investigation based on lagged data may lead to results that support the hypothesis. This offers a good starting point for further and more concentrated research in this area.

5. Conclusion

The investigation of a sample of political events, that captures supranational influence on companies within the European market, supports the thesis that SOEs are less effected by uncertainty introduced by political events. The occurring effect, however, is only statistically provable when the consideration takes place on group level (SOE vs non-SOE). The following regression analysis fails to support the evidence on group level. The significance found in a single regressor model when using OLS regression vanishes when adding control variables. Although a positive coefficient is observable in all models and a p-value under 0.1 is reached, this work refrains from taking this as sufficient evidence. On the other hand, the work indicates that daily sentiment retrieved from social media influences abnormal returns during a political event. Investigating both variables (SOE and TEMPER) in interaction does not support the theory that the level of sentiment plays a role for the relevance of state-ownership when explaining abnormal returns. This work offers a good starting point for future research. Firstly, the result on group level shows that the hypothesis was not unrealistic. A deeper dive on what common company characteristics created the divergence between the group analysis and regression analysis could be important to further understand abnormal returns during political events. Furthermore, using a different sample of SOEs with governmental ownership over 50% could yield better results, as the second set of regressions indicated. The focus on the Stoxx600, limited possibilities in this regard. The by far biggest limitation of this work was the restricted access to twitter data. The results, however, showed big potential for further research into the explanatory power of sentiment in context of abnormal returns.

6. References

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7. Appendices

Appendix 1: Abbreviations

AR	Abnormal Return
AAR	Average Abnormal Return
CAR	Cumulative Abnormal Return
CAAR	Cumulative Average Abnormal Return
EP	European Parliament
EP2014	European Parliament Election 2014
EP2019	European Parliament Election 2019
Bre2016	EU referendum 2016
Non-SOE	Non State-Owned-Enterprise
SOE	State-Owned-Enterprise

Table 1: AARs of the main sample

t	SOE_AAR	Non-SOE_AAR	t	SOE_AAR	Non-SOE_AAR
-10	-0.0018	-0.0019*	0	0.0062**	0.0024***
	(-1.4133)	(-2.2256)		(2.9880)	(5.1317)
-9	0.0008	-0.0006	1	-0.0023	0.0011
	(0.6228)	(-1.5694)		(-0.8561)	(1.0177)
-8	-0.0043**	-0.0025***	2	0.0004	-0.004***
	(-3.1155)	(-6.3860)		(0.2134)	(-4.2250)
-7	-0.0066***	-0.0044***	3	0.0010	0.0008
	(-4.0628)	(-9.1441)		(0.5493)	(1.7789)
-6	-0.0008	-0.003***	4	0.0021	-0.0006
	(-0.4815)	(-5.3140)		(1.1649)	(-1.1529)
-5	-0.0013	-0.0025***	5	0.0017	0.0004
	(-0.8599)	(-5.2127)		(1.1766)	(0.8717)
-4	0.0031	0.0034***	6	-0.0018	0.0025***
	(1.6829)	(5.0498)		(-1.1086)	(3.8565)
-3	-0.0028	-0.0023***	7	0.0028*	-0.0028***
	(-1.4779)	(-3.3596)		(2.5066)	(-4.3628)
-2	-0.0042**	-0.0028***	8	-0.0002	-0.0011*
	(-2.8376)	(-6.1072)		(-0.1313)	(-2.4496)
-1	0.0017	0.0000	9	0.0026*	0.001
	(1.3632)	(0.0000)		(1.9784)	(1.5320)
			10	0.0019	0.0011
				(1.5247)	(1.6676)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per AAR: 160, 1442. Event Dates: 25.05.2014, 23.06.2016, 26.05.2019

Table 2: CAARs of the main sample

Window	SOE_CAAR	Non-SOE_CAAR
[-10;10]	-0.0017 (-0.2025)	-0.016*** (-6.4035)
[-5,5]	0.0056 (0.6751)	-0.0041* (-2.1330)
[-1;1]	0.0056 (1.4268)	0.0035** (2.8835)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observations Non-SOE: 1442. Observations SOE: 160. Event Dates: 25.05.2014, 23.06.2016, 26.05.2019

Table 3: Parametric Tests for Main Sample – SOE group

		SOE	
Window	Patell Z	adjusted Patell Z	BMP
[-10;10]	-0.6428	-0.5052	-0.6705
[-5,5]	0.4016	0.3157	0.3405
[-1;1]	1.8641	1.4652	1.6846

Market Model is used. Observations SOE: 160. Event Dates: 25.05.2014, 23.06.2016, 26.05.2019

Table 4: Parametric Tests for the Main Sample - non-SOE group

		Non-SOE	
Window	Patell Z	adjusted Patell Z	BMP
[-10;10]	-5.711	-2.005	-5.0283
[-5,5]	-0.6326	-0.2213	-0.5757
[-1;1]	4.0461	1.4151	2.969

Market Model is used. Observations Non-SOE: 1442. Event Dates: 25.05.2014, 23.06.2016, 26.05.2019

Table 5: Comparison of the single events in the main sample

Window	EP2014	Brexit	EP2019	Complete Sample
[-10;10]	-0.0002	-0.0352***	-0.0084*	-0.0146***
	(-0.0907)	(-6.2955)	(-2.2905)	(-6.0492)
[-5,5]	0.0154***	-0.0221***	-0.0035	-0.0031
	(6.7860)	(-5.6123)	(-1.0167)	(-1.6322)
[-1;1]	0.007***	-0.0006	0.0046**	0.0037**
	(6.9326)	(-0.2261)	(2.7044)	(3.1981)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observations: 561, 540, 502, 1602. Event Dates: 25.05.2014, 23.06.2016, 26.05.2019

Table 6: AARs (not differentiated) of EP2014

t	AAR	t	AAR
-10	0.0013* (2.2045)	0	0.0037*** (5.7533)
-9	-0.0015** (-2.6460)	1	0.0017** (3.0318)
-8	-0.0023*** (-3.5816)	2	0.0007 (0.9300)
-7	-0.0075*** (-8.4494)	3	-0.0001 (-0.1785)
-6	-0.0067*** (-8.2954)	4	0.0025*** (4.3086)
-5	0.0028*** (4.2604)	5	-0.0001 (-0.2027)
-4	0.0013 (1.8982)	6	-0.0011* (-2.3184)
-3	-0.0012 (-1.8526)	7	-0.0009 (-1.7661)
-2	0.0025*** (4.2535)	8	0.0031*** (5.8563)
-1	0.0017*** (3.5633)	9	0.0001 (0.1910)
		10	-0.0002 (-0.3172)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per AAR: 561. Event Dates: 25.05.2014

Table 7: AARs (differentiated) of EP2014

t	SOE_AAR	Non-SOE_AAR	t	SOE_AAR	Non-SOE_AAR
-10	-0.0004	0.0015*	0	0.0074**	0.0033***
	(-0.2445)	(2.3833)		(3.4613)	(4.9091)
-9	-0.0020	-0.0015**	1	-0.0005	0.0019**
	(-0.7928)	(-2.6533)		(-0.2623)	(3.2447)
-8	-0.0039	-0.0021**	2	-0.0032	0.0012
	(-1.6665)	(-3.1581)		(-1.2640)	(1.5265)
-7	-0.0156***	-0.0066***	3	0.0003	-0.0002
	(-4.7943)	(-7.2522)		(0.1449)	(-0.3453)
-6	-0.0067*	-0.0067***	4	0.0036	0.0024***
	(-2.0236)	(-8.1699)		(1.5530)	(4.0554)
-5	0.0038	0.0027***	5	0.0008	-0.0002
	(1.8917)	(3.8807)		(0.4208)	(-0.3950)
-4	0.0033	0.0011	6	-0.0033	-0.0009
	(1.0456)	(1.6264)		(-1.8711)	(-1.8407)
-3	-0.0023	-0.0011	7	0.0024	-0.0013*
	(-0.8836)	(-1.6667)		(1.3992)	(-2.4473)
-2	0.0024	0.0025***	8	0.0072***	0.0027***
	(0.9467)	(4.2341)		(3.7288)	(4.9576)
-1	0.0046**	0.0013**	9	0.0029	-0.0002
	(2.6789)	(2.6361)		(1.5027)	(-0.3704)
			10	-0.0003	-0.0002
				(-0.2375)	(-0.2913)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per AAR: 56, 505. Event Dates: 25.05.2014

Table 8: CAARs of EP2014

Window	SOE_CAAR	Non-SOE_CAAR
[-10;10]	0.0005 (0.0468)	-0.0003 (-0.1183)
[-5,5]	0.0201* (2.1683)	0.0149*** (6.4557)
[-1;1]	0.0114** (3.4195)	0.0066*** (6.1575)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per CAAR: 56, 505. Event Dates: 25.05.2014

Table 9: AARs (not differentiated) for the Bre2016

t	AAR	t	AAR
-10	-0.0036 (-1.6818)	0	0.0021** (2.9288)
-9	-0.0008 (-1.3241)	1	-0.0012 (-0.4193)
-8	-0.0025*** (-3.7616)	2	-0.0116*** (-5.2991)
-7	-0.0034*** (-4.9739)	3	0.0015 (1.5691)
-6	-0.0008 (-1.0261)	4	-0.0026* (-2.2101)
-5	-0.0088*** (-9.9263)	5	0.0028** (3.2144)
-4	0.0067*** (4.1526)	6	0.0051*** (3.4524)
-3	-0.0029 (-1.7668)	7	-0.0055*** (-3.5696)
-2	-0.0064*** (-8.5271)	8	-0.0048*** (-4.9754)
-1	-0.0015 (-1.8310)	9	0.002 (1.2511)
		10	0.0014 (0.9168)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per AAR: 540. Event Dates: 23.06.2016

Table 10: AARs (differentiated) for the Bre2016

t	SOE_AAR	Non-SOE_AAR	t	SOE_AAR	Non-SOE_AAR
-10	-0.0039 (-1.6031)	-0.0036 (-1.5315)	0	0.0042 (1.4477)	0.0018* (2.4585)
-9	0.0000 (0.0000)	-0.0009 (-1.4218)	1	-0.0091 (-1.2395)	-0.0004 (-0.1305)
-8	-0.0043 (-1.5614)	-0.0024*** (-3.5502)	2	0.0060 (1.2963)	-0.0134*** (-5.6915)
-7	-0.0038 (-1.4439)	-0.0034*** (-4.8282)	3	-0.0028 (-0.8685)	0.0019 (1.9007)
-6	0.0035 (1.3375)	-0.0013 (-1.5957)	4	-0.0033 (-0.8072)	-0.0026* (-2.1164)
-5	-0.0115*** (-3.7347)	-0.0086*** (-9.2972)	5	0.0013 (0.4168)	0.003*** (3.3109)
-4	0.0011 (0.2727)	0.0072*** (4.1611)	6	0.0030 (1.1077)	0.0053** (3.2983)
-3	-0.0023 (-0.4669)	-0.0030 (-1.7244)	7	0.0032 (1.3346)	-0.0064*** (-3.8137)
-2	-0.0078*** (-3.5345)	-0.0063*** (-7.9085)	8	-0.0056 (-1.6462)	-0.0047*** (-4.6735)
-1	-0.0030 (-1.7439)	-0.0014 (-1.5787)	9	0.0027 (0.8820)	0.0019 (1.0939)
			10	0.0012 (0.6457)	0.0014 (0.8356)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per AAR: 51, 489. Event Dates: 23.06.2016

Table 11: CAARs of Bre2016

Window	SOE_CAAR	Non-SOE_CAAR
[-10;10]	-0.0312 (-1.8132)	-0.0356*** (-6.0236)
[-5,5]	-0.0273* (-2.0811)	-0.0215*** (-5.2182)
[-1;1]	-0.0079 (-1.1632)	0.0001 (0.0387)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per CAAR: 51, 489. Event Dates: 23.06.2016

Table 12: AARs (not differentiated) for the EP2019

t	AAR	t	AAR
-10	-0.0035*** (-5.3844)	0	0.0024* (2.2492)
-9	0.0011 (1.4890)	1	0.0018* (2.4981)
-8	-0.0032*** (-4.8497)	2	0.0003 (0.2613)
-7	-0.0028*** (-3.5196)	3	0.0012 (1.6100)
-6	-0.0006 (-0.5165)	4	-0.0010 (-1.3846)
-5	-0.0014 (-1.9148)	5	-0.0014 (-1.6137)
-4	0.0022** (3.2450)	6	0.0024* (2.5231)
-3	-0.0029*** (-3.7611)	7	-0.0001 (-0.1501)
-2	-0.0051*** (-5.7857)	8	-0.0017** (-2.6632)
-1	0.0004 (0.5468)	9	0.0014* (2.2206)
		10	0.0025*** (3.3656)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per AAR: 502. Event Dates: 26.05.2019

Table 13: AARs (differentiated) for the EP2019

t	SOE_AAR	Non-SOE_AAR	t	SOE_AAR	Non-SOE_AAR
-10	-0.0011	-0.0038***	0	0.0068	0.0018
	(-0.4357)	(-5.7335)		(1.3150)	(1.7555)
-9	0.0046*	0.0007	1	0.0025	0.0017*
	(2.3548)	(0.8844)		(0.7429)	(2.4191)
-8	-0.0048*	-0.003***	2	-0.0013	0.0005
	(-2.2783)	(-4.3174)		(-0.6089)	(0.3972)
-7	0.0001	-0.0032***	3	0.0053	0.0007
	(0.0538)	(-3.7165)		(1.3440)	(1.0141)
-6	0.0012	-0.0008	4	0.0058*	-0.0018*
	(0.4999)	(-0.6310)		(2.0943)	(-2.4644)
-5	0.0032	-0.0019*	5	0.0030	-0.0019*
	(1.4332)	(-2.4652)		(1.2067)	(-2.0599)
-4	0.0048*	0.0019**	6	-0.0047	0.0032***
	(2.1451)	(2.6761)		(-1.2817)	(3.3142)
-3	-0.0037*	-0.0029***	7	0.0027	-0.0005
	(-2.1061)	(-3.4639)		(1.5840)	(-0.6982)
-2	-0.0077**	-0.0048***	8	-0.0027	-0.0015*
	(-2.8781)	(-5.1419)		(-1.2374)	(-2.2514)
-1	0.0031	0.0001	9	0.0022	0.0013
	(1.1171)	(0.1335)		(1.2487)	(1.9289)
			10	0.0049	0.0022**
				(1.6264)	(2.9304)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per AAR: 53,449. Event Dates: 26.05.2019

Table 14: CAARs for EP2019

Window	SOE_CAAR	Non-SOE_CAAR
[-10;10]	0.0243	-0.0123***
	(1.4798)	(-3.4280)
[-5,5]	0.0219	-0.0065*
	(1.1661)	(-2.0803)
[-1;1]	0.0125	0.0036*
	(1.3763)	(2.3354)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per CAAR: 53,448. Event Dates: 26.05.2019

Table 15: Sub-Sample Event List

	Event	Date	Reasoning
Crises	Portugal requests Bailout	2011-04-07	Unannounced Event within the Debt Crisis
	Euromaidan	2014-02-18	Unannounced Protest leading to the Revolution
	Vessel sinking Lampedusa	2015-04-18	Unannounced Event within the migration crisis
EP Votes	ESM Treaty	2011-03-23	EU Parliament approves Treaty change
	OTC derivatives regulation	2012-03-29	EU Parliament adopts the regulation
	CETA	2017-02-15	EU Parliament approves the trade agreement
	Trade Agreement Singapore	2019-02-13	EU Parliament approves the trade agreement

Criteria for Event selection for Crises: Three major crises were found when analyzing the data. For each of the Crisis one unannounced event was picked. Criteria for the EP Votes: (1) Must be a parliamentary vote. (2) In the list of the European Union website (mentioned in chapter 3). Criteria for both samples: (1) Not intersecting with the main sample (2) Similar size to the main sample. Furthermore, events were removed when other important market events were in the event period.

Table 16: AARs (differentiated) of the sub-sample EP Votes

t	SOE_AAR	Non-SOE_AAR	t	SOE_AAR	Non-SOE_AAR
-10	0.0003 (0.2935)	0.0018*** (5.2128)	0	-0.0011 (-0.8576)	-0.0009** (-2.5966)
-9	0.0021 (1.8740)	-0.0008* (-2.0229)	1	0.0009 (1.0060)	0.0015*** (4.2054)
-8	0.002 (1.9426)	0.0007* (1.9920)	2	-0.006*** (-5.1478)	-0.004*** (-8.4061)
-7	0.0029* (2.1669)	0.001** (2.6790)	3	0.0044*** (4.0797)	0.0021*** (6.4701)
-6	-0.0016 (-1.1069)	-0.0001 (-0.2423)	4	-0.0005 (-0.3842)	-0.0021*** (-4.2121)
-5	0.0013 (1.0560)	0.0001 (0.2650)	5	-0.003** (-2.7190)	-0.0016** (-2.6342)
-4	-0.0003 (-0.2174)	-0.0003 (-0.7696)	6	0.0028 (1.2744)	0.0022*** (4.2426)
-3	-0.0011 (-0.8705)	0.0015*** (3.6526)	7	0.0002 (0.1592)	-0.0011** (-3.0773)
-2	0.0015 (1.2344)	0.0000 (0.0000)	8	0.0023 (1.1276)	0.0023*** (6.6198)
-1	0.0010 (0.8474)	0.0001 (0.3042)	9	0.001 (0.5349)	-0.0009** (-2.5966)
			10	0.0004 (0.3122)	-0.0004 (-1.0456)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per AAR: 222, 1987. Event Dates: 23.03.2011, 29.03.2012, 15.02.2017, 13.02.2019

Table 17: CAARs of EP Votes

Window	SOE_CAAR	Non-SOE_CAAR
[-10;10]	0.0096 (1.4320)	0.0011 (0.5390)
[-5,5]	-0.0029 (-0.6785)	-0.0036* (-2.4040)
[-1;1]	0.0008 (0.4580)	0.0006 (1.1318)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per CAAR: 222, 1987. Event Dates: 23.03.2011, 29.03.2012, 15.02.2017, 13.02.2019

Table 18: AARs (differentiated) of the sub-sample Crises

t	SOE_AAR	Non-SOE_AAR
0	-0.0026	-0.0012***
	(-1.8289)	(-3.0944)
1	-0.0034*	0.0004
	(-2.2388)	(1.0708)
2	0.0007	-0.0021***
	(0.2935)	(-4.6080)
3	0.0008	0.002***
	(0.5564)	(4.8574)
4	0.0028	0.0008
	(1.5992)	(1.7141)
5	0.0005	-0.0003
	(0.3353)	(-0.7941)
6	0.0012	-0.0006
	(0.7897)	(-1.3791)
7	-0.0026	-0.0007
	(-1.5173)	(-1.5373)
8	0.0033*	0.0031***
	(1.9822)	(7.0458)
9	0.0029	0.0005
	(1.5420)	(1.1780)
10	-0.0044**	-0.0003
	(-2.8561)	(-0.7280)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per AAR: 168, 1534. Event Dates: 07.04.2011, 18.02.2014, 18.04.2015

Table 19: CAARs of Crises

Window	SOE_CAAR	Non-SOE_CAAR
[0;10]	0.0039 (0.4455)	0.0019 (1.1750)
[0;5]	0.0037 (0.6644)	-0.0009 (-0.8580)
[0;2]	-0.0023 (-0.7379)	-0.0028*** (-3.7977)
[0;1]	-0.0026 (-1.2615)	-0.0022*** (-3.8080)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market Model is used. Observation per CAAR: 168, 1534. Event Dates: 07.04.2011, 18.02.2014, 18.04.2015

Table 20: CAARs of the main sample under different models

Window	(1) Market	(2) Market-adjusted	(3) Mean-adjusted
[-10;10]	-0.0146***	-0.0132***	-0.0366***
	(-6.0492)	(-5.0144)	(-13.0037)
[-5,5]	-0.0031	-0.0034	-0.0068***
	(-1.6322)	(-1.7285)	(-3.4161)
[-1;1]	0.0037**	0.0048***	-0.0128***
	(3.1981)	(3.9565)	(-8.8734)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Observation per CAAR: 1603. Event Dates: 25.05.2014, 23.06.2016, 26.05.2019

Table 21: AARs (differentiated) for the main sample – Market-adjusted model

t	SOE_AAR	Non-SOE_AAR	t	SOE_AAR	Non-SOE_AAR
-10	-0.0017	-0.0018*	0	0.0056**	0.002***
	(-1.2735)	(-2.1061)		(2.6012)	(4.0983)
-9	0.0007	0.0000	1	-0.0019	0.0028*
	(0.5071)	(0.0000)		(-0.5527)	(2.3175)
-8	-0.0044**	-0.002***	2	0.0013	-0.0035***
	(-2.8707)	(-4.8358)		(0.6426)	(-3.7230)
-7	-0.0064***	-0.0037***	3	0.0006	0.0005
	(-3.8200)	(-7.4451)		(0.3210)	(1.1617)
-6	-0.0014	-0.0032***	4	0.0020	-0.0013**
	(-0.8649)	(-5.6229)		(1.2474)	(-2.7739)
-5	-0.0006	-0.0024***	5	0.0015	0.0003
	(-0.3961)	(-4.8823)		(1.0672)	(0.6507)
-4	0.0025	0.0032***	6	-0.0020	0.0024***
	(1.2883)	(4.6521)		(-1.2585)	(3.6940)
-3	-0.0037	-0.0031***	7	0.0025*	-0.0026***
	(-1.8349)	(-4.5558)		(2.2764)	(-4.0796)
-2	-0.0034*	-0.0029***	8	-0.0004	-0.0009
	(-2.2390)	(-6.0956)		(-0.2365)	(-1.9012)
-1	0.0013	0.0000	9	0.002	0.0014*
	(1.0401)	(-0.0103)		(1.5854)	(2.0566)
			10	0.0018	0.0009
				(1.3815)	(1.3478)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market-adjusted model is used. Observation per AAR: 160, 1443. Event Dates: 25.05.2014, 23.06.2016, 26.05.2019

Table 22: CAARs (differentiated) for the main sample – Market-adjusted model

Window	SOE_CAAR	Non-SOE_CAAR
[-10;10]	-0.004	-0.0142***
	(-0.4480)	(-5.1683)
[-5,5]	0.0052	-0.0044*
	(0.6416)	(-2.1803)
[-1;1]	0.005	0.0048***
	(1.1821)	(3.7799)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Market-adjusted model is used. Observation per CAAR: 160, 1443. Event Dates: 25.05.2014, 23.06.2016, 26.05.2019

Table 23: AARs (differentiated) for the main sample – Mean-adjusted model

t	SOE_AAR	Non-SOE_AAR	t	SOE_AAR	Non-SOE_AAR
-10	-0.0063***	-0.0069***	0	0.0124***	0.009***
	(-4.0895)	(-7.6561)		(5.7402)	(17.8575)
-9	-0.0038*	-0.0053***	1	-0.0267***	-0.0252***
	(-2.1172)	(-9.6488)		(-5.8080)	(-16.8040)
-8	-0.0096***	-0.0078***	2	-0.0158***	-0.019***
	(-5.4462)	(-16.2752)		(-6.9133)	(-16.8102)
-7	-0.0123***	-0.0103***	3	0.0091***	0.0083***
	(-5.9709)	(-17.0768)		(4.5233)	(15.0390)
-6	0.0004	-0.0012*	4	0.0091***	0.0074***
	(0.2436)	(-2.0465)		(5.1549)	(13.1519)
-5	-0.0072***	-0.0093***	5	0.0057***	0.0041***
	(-4.7129)	(-18.2526)		(3.9484)	(8.4772)
-4	0.0076***	0.0086***	6	0.0001	0.0047***
	(3.6426)	(11.8419)		(0.0611)	(6.9952)
-3	0.0085***	0.0101***	7	0.0009	-0.0044***
	(3.8655)	(12.9865)		(0.7470)	(-6.6247)
-2	-0.0051**	-0.0048***	8	-0.004*	-0.0043***
	(-2.7965)	(-8.8203)		(-2.0171)	(-7.4513)
-1	0.0046***	0.0031***	9	0.0018	-0.0002
	(3.6586)	(7.4374)		(1.2058)	(-0.2771)
			10	0.0064***	0.0056***
				(4.7442)	(8.1352)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Mean-adjusted model is used. Observation per AAR: 160, 1443. Event Dates: 25.05.2014, 23.06.2016, 26.05.2019

Table 24: CAARs (differentiated) for the main sample – Mean-adjusted model

Window	SOE_CAAR	Non-SOE_CAAR
[-10;10]	-0.0242*	-0.0379***
	(-2.4177)	(-12.9981)
[-5,5]	0.0021	-0.0078***
	(0.2611)	(-3.8432)
[-1;1]	-0.0097	-0.0131***
	(-1.8954)	(-8.7708)

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. Mean-adjusted model is used. Observation per CAAR: 160, 1443. Event Dates: 25.05.2014, 23.06.2016, 26.05.2019

Table 25: Regression at 20% governmental ownership - OLS

	(1) CAR	(2) CAR	(3) CAR	(4) CAR
ß1SOE	0.0142	0.0116	0.0120	0.0122
	(1.77)	(1.45)	(1.51)	(1.54)
ß2SIZE		1.68e-13***	1.71e-13***	1.71e-13***
		(4.06)	(4.17)	(4.18)
ß3Growth			-0.0000476	-0.0000489
			(-0.68)	(-0.71)
ß4Leverage				0.000000166
				(0.40)
_cons	-0.0160***	-0.0200***	-0.0207***	-0.0202***
	(-6.30)	(-7.27)	(-7.49)	(-7.30)
N	1602	1593	1580	1560

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. CAR is the dependent variable. Regressors are described in chapter 3. In each subsequent regression, one control variable is added.

Table 26: Regression at 20% governmental ownership - fixed effects

	(1) CAR	(2) CAR	(3) CAR	(4) CAR
B1SOE	0.0851*	0.0837*	0.0840*	0.103*
	(2.22)	(2.18)	(2.20)	(2.58)
B2SIZE		2.50e-13	2.74e-13	3.14e-13
		(1.22)	(1.34)	(1.54)
B3Growth			-0.000289	-0.000289
			(-1.78)	(-1.79)
B4Leverage				-1.03e-08
				(-0.02)
_cons	-0.0231***	-0.0296***	-0.0305***	-0.0331***
	(-5.14)	(-4.12)	(-4.23)	(-4.46)
N	1602	1593	1580	1560

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. CAR is the dependent variable. Regressors are described in chapter 3. In each subsequent regression, one control variable is added.

Table 27: Regression at 20% governmental ownership - random effects

	(1) CAR	(2) CAR	(3) CAR	(4) CAR
ß1SOE	0.0149	0.0122	0.0125	0.0128
	(1.76)	(1.45)	(1.50)	(1.54)
ß2SIZE		1.68e-13***	1.72e-13***	1.72e-13***
		(3.88)	(3.99)	(4.00)
ß3Growth			-0.0000525	-0.0000542
			(-0.75)	(-0.78)
ß4Leverage				0.000000149
				(0.36)
_cons	-0.0161***	-0.0201***	-0.0208***	-0.0202***
	(-5.97)	(-6.94)	(-7.18)	(-6.97)
N	1602	1593	1580	1560

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. CAR is the dependent variable. Regressors are described in chapter 3. In each subsequent regression, one control variable is added.

Table 28: Regression at 20% governmental ownership with time effects

	(1) CAR	(2) CAR	(3) CAR
B1SOE	0.0117	0.0915*	0.0124
	(1.50)	(2.32)	(1.49)
B2SIZE	1.69e-13***	2.47e-13	1.69e-13***
	(4.18)	(1.22)	(3.93)
B3Growth	-0.0000474	-0.000271	-0.0000541
	(-0.69)	(-1.70)	(-0.79)
B4Leverage	0.000000104	-0.000000103	7.84e-08
	(0.26)	(-0.21)	(0.19)
2014bn.year	.	.	.
	.	.	.
2016.year	-0.0355***	-0.0349***	-0.0355***
	(-6.21)	(-6.19)	(-6.42)
2019.year	-0.00817	-0.00753	-0.00820
	(-1.40)	(-1.28)	(-1.45)
_cons	-0.00552	-0.0159*	-0.00558
	(-1.31)	(-2.00)	(-1.31)
N	1560	1560	1560

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. CAR is the dependent variable. Regressors are described in chapter 3. (1) OLS regression, (2) fixed effects regression (3) random effects regression.

Table 29: Regression at 30% governmental ownership -OLS

CAR is the dependent variable. Regressors are described in chapter 3. SIZE2 is market capitalization divided by 100million. In each subsequent regression, one control variable is added.

	(1) CAR	(2) CAR	(3) CAR	(4) CAR
ß1SOE	0.0189*	0.0150	0.0153	0.0159
	(2.01)	(1.60)	(1.63)	(1.70)
ß2SIZE2		0.0000166***	0.0000169***	0.0000169***
		(4.01)	(4.11)	(4.12)
ß3Growth			-0.0000471	-0.0000483
			(-0.68)	(-0.70)
ß4Leverage				0.000000165
				(0.40)
_cons	-0.0159***	-0.0199***	-0.0205***	-0.0200***
	(-6.37)	(-7.32)	(-7.53)	(-7.35)
N	1602	1593	1580	1560
R-sq	0.003	0.012	0.013	0.014
adj. R-sq	0.002	0.011	0.012	0.011

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 30: Regression at 30% governmental ownership -fixed effects

CAR is the dependent variable. Regressors are described in chapter 3. SIZE2 is market capitalization divided by 100million. In each subsequent regression, one control variable is added.

	(1) CAR	(2) CAR	(3) CAR	(4) CAR
ß1SOE	0.0435	0.0417	0.0433	0.0558
	(1.20)	(1.14)	(1.19)	(1.47)
ß2SIZE2		0.0000254	0.0000277	0.0000311
		(1.24)	(1.35)	(1.52)
ß3Growth			-0.000292	-0.000298
			(-1.80)	(-1.84)
ß4Leverage				-1.42e-08
				(-0.03)
_cons	-0.0176***	-0.0242***	-0.0252***	-0.0264***
	(-5.08)	(-3.66)	(-3.80)	(-3.93)
N	1602	1593	1580	1560

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 31: Regression at 30% governmental ownership - random effects

	(1) CAR	(2) CAR	(3) CAR	(4) CAR
ß1SOE	0.0194	0.0154	0.0157	0.0163
	(1.95)	(1.56)	(1.60)	(1.67)
ß2SIZE2		0.0000166***	0.0000170***	0.0000170***
		(3.83)	(3.95)	(3.95)
ß3Growth			-0.0000520	-0.0000536
			(-0.74)	(-0.77)
ß4Leverage				0.000000149
				(0.36)
_cons	-0.0159***	-0.0199***	-0.0205***	-0.0200***
	(-6.03)	(-6.99)	(-7.22)	(-7.02)
N	1602	1593	1580	1560

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. CAR is the dependent variable. Regressors are described in chapter 3. SIZE2 is market capitalization divided by 100million. In each subsequent regression, one control variable is added.

Table 32: Regression models at 30% governmental ownership with time-fixed effects

	(1) CAR	(2) CAR	(3) CAR
ß1SOE	0.0151	0.0429	0.0155
	(1.63)	(1.15)	(1.58)
ß2SIZE2	0.0000167***	0.0000243	0.0000167***
	(4.12)	(1.20)	(3.89)
ß3Growth	-0.0000470	-0.000280	-0.0000537
	(-0.69)	(-1.75)	(-0.78)
ß4Leverage	0.000000104	-0.000000106	7.85e-08
	(0.25)	(-0.22)	(0.19)
2014bn.year	.	.	.
	.	.	.
2016.year	-0.0354***	-0.0351***	-0.0354***
	(-6.19)	(-6.20)	(-6.40)
2019.year	-0.00801	-0.00742	-0.00803
	(-1.37)	(-1.26)	(-1.42)
_cons	-0.00542	-0.00945	-0.00544
	(-1.29)	(-1.29)	(-1.29)
N	1560	1560	1560

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. CAR is the dependent variable. Regressors are described in chapter 3. SIZE2 is market capitalization divided by 100million. In each subsequent regression, one control variable is added. (1) OLS regression, (2) fixed effects regression (3) random effects regression.

Table 33: Regression with restricted indices -OLS

	(1) CAR	(2) CAR	(3) CAR	(4) CAR
ß1SOE	0.0100	0.0109	0.0113	0.0117
	(1.17)	(1.28)	(1.34)	(1.38)
ß2SIZE2		0.0000174***	0.0000178***	0.0000177***
		(4.22)	(4.32)	(4.34)
ß3Growth			-0.0000480	-0.0000493
			(-0.69)	(-0.71)
ß4Leverage				0.000000166
				(0.40)
_cons	-0.0154***	-0.0200***	-0.0206***	-0.0201***
	(-6.13)	(-7.21)	(-7.43)	(-7.25)
N	1602	1593	1580	1560

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. CAR is the dependent variable. Regressors are described in chapter 3. SIZE2 is market capitalization divided by 100million. In each subsequent regression, one control variable is added. The model excludes companies listed at the Swiss and Norwegian stock exchange.

Table 34: Regression with restricted indices -fixed effects

	(1)	(2)	(3)	(4)
	CAR	CAR	CAR	CAR
ß1SOE	0.0851*	0.0837*	0.0840*	0.103*
	(2.22)	(2.18)	(2.20)	(2.58)
ß2SIZE2		0.0000250	0.0000274	0.0000314
		(1.22)	(1.34)	(1.54)
ß3Growth			-0.000289	-0.000289
			(-1.78)	(-1.79)
ß4Leverage				-1.03e-08
				(-0.02)
_cons	-0.0219***	-0.0285***	-0.0294***	-0.0317***
	(-5.40)	(-4.10)	(-4.22)	(-4.44)
N	1602	1593	1580	1560

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. CAR is the dependent variable. Regressors are described in chapter 3. SIZE2 is market capitalization divided by 100million. In each subsequent regression, one control variable is added. The model excludes companies listed at the Swiss and Norwegian stock exchange.

Table 35: Regression with restricted indices -random effects

	(1) CAR	(2) CAR	(3) CAR	(4) CAR
ß1SOE	0.0109	0.0116	0.0120	0.0124
	(1.20)	(1.30)	(1.35)	(1.40)
ß2SIZE2		0.0000175***	0.0000178***	0.0000178***
		(4.03)	(4.15)	(4.16)
ß3Growth			-0.0000528	-0.0000546
			(-0.76)	(-0.79)
ß4Leverage				0.000000149
				(0.36)
_cons	-0.0155***	-0.0201***	-0.0207***	-0.0202***
	(-5.80)	(-6.89)	(-7.12)	(-6.92)
N	1602	1593	1580	1560

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. CAR is the dependent variable. Regressors are described in chapter 3. SIZE2 is market capitalization divided by 100million. In each subsequent regression, one control variable is added. The model excludes companies listed at the Swiss and Norwegian stock exchange.

Table 36: Regression all models restricted indices -time fixed effects

	(1) CAR	(2) CAR	(3) CAR
ß1SOE	0.0111	0.0915*	0.0119
	(1.32)	(2.32)	(1.34)
ß2SIZE2	0.0000175***	0.0000247	0.0000176***
	(4.33)	(1.22)	(4.08)
ß3Growth	-0.0000478	-0.000271	-0.0000544
	(-0.70)	(-1.70)	(-0.79)
ß4Leverage	0.000000104	-0.000000103	7.80e-08
	(0.25)	(-0.21)	(0.19)
2014bn.year	.	.	.
	.	.	.
2016.year	-0.0355***	-0.0349***	-0.0355***
	(-6.21)	(-6.19)	(-6.42)
2019.year	-0.00819	-0.00753	-0.00822
	(-1.40)	(-1.28)	(-1.45)
_cons	-0.00547	-0.0146	-0.00554
	(-1.30)	(-1.91)	(-1.30)
N	1560	1560	1560

Note: t-scores in parentheses. *, **, and *** indicate significance at the 5%, 1% and 0.1% level. CAR is the dependent variable. Regressors are described in chapter 3. SIZE2 is market capitalization divided by 100million. In each subsequent regression, one control variable is added. The model excludes companies listed at the Swiss and Norwegian stock exchange. (1) OLS regression, (2) fixed effects regression (3) random effects regression.

Table 37: TEMPER variable by day

Date	1	-1	0	Total	Temper
6/8/2016	299	262	397	958	0.03862213
6/9/2016	575	853	1118	2546	-0.1091909
6/10/2016	216	248	293	757	-0.0422721
6/13/2016	196	361	443	1000	-0.165
6/14/2016	516	323	492	1331	0.14500376
6/15/2016	1206	1375	1282	3863	-0.0437484
6/16/2016	513	678	553	1744	-0.0946101
6/17/2016	195	327	246	768	-0.171875
6/20/2016	243	638	535	1416	-0.2789548
6/21/2016	763	1116	1261	3140	-0.1124204
6/22/2016	694	1169	1164	3027	-0.156921
6/23/2016	743	800	1432	2975	-0.0191597
6/24/2016	9217	6660	8664	24541	0.10419298
6/27/2016	1015	1800	1508	4323	-0.1815869
6/28/2016	802	1167	1389	3358	-0.1086957
6/29/2016	878	1748	1171	3797	-0.2291283
6/30/2016	1046	1024	1280	3350	0.00656716
7/1/2016	780	808	1090	2678	-0.0104556
7/4/2016	773	1102	1021	2896	-0.113605
7/5/2016	623	886	942	2451	-0.1073031
7/6/2016	366	443	681	1490	-0.0516779
7/7/2016	999	650	769	2418	0.14433416
Total	22359	24176	27334	73869	-0.0245976

Note: TEMPER is the is the sentiment variable retrieved from tweets. The definition is found in chapter 3. 1 indicates positive tweets, -1 negative tweets and 0 neutral tweets.

Table 38: Regression with TEMPER

AR is the dependent variable. Regressors are described in chapter 3. SIZE is divided by 10million. In each subsequent regression, one control variable is added. SOE threshold 30% state ownership.

	(1) AR	(2) AR	(3) AR	(4) AR
TEMPER	0.0110***	0.0106***	0.0102***	0.0100***
	(3.93)	(3.82)	(3.66)	(3.58)
Size		0.000000201***	0.000000205***	0.000000206***
		(3.70)	(3.79)	(3.79)
Growth			-0.00000653	-0.00000697
			(-0.47)	(-0.50)
Leverage				-0.000000892
				(-0.89)
_cons	-0.000842*	-0.00136***	-0.00146***	-0.00135**
	(-2.26)	(-3.42)	(-3.67)	(-3.17)
N	11309	11246	11120	11015
R-sq	0.001	0.003	0.003	0.003
adj. R-sq	0.001	0.002	0.002	0.002

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 39: Regression model with interaction term

Note: AR is the dependent variable. SOE threshold 30% state ownership. SOE#c.TEMPER is the interaction term.

Source	SS	df	MS			
				Number of obs	=	11,309
				F(3, 11305)	=	5.63
Model	.017997612	3	.005999204	Prob > F	=	0.0007
Residual	12.0416805	11,305	.001065164	R-squared	=	0.0015
				Adj R-squared	=	0.0012
Total	12.0596781	11,308	.001066473	Root MSE	=	.03264

AR	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.SOE	.0000284	.0015152	0.02	0.985	-.0029417	.0029984
TEMPER	.011722	.0028936	4.05	0.000	.00605	.017394
SOE#c.TEMPER						
1	-.0109933	.0113507	-0.97	0.333	-.0332426	.0112561
_cons	-.0008441	.0003862	-2.19	0.029	-.0016011	-.0000871

Table 40: Regression model with interaction (TEMPER as binary)

Note: AR is the dependent variable. SOE threshold 30% state ownership. SOE#c.TEMPERpos is the interaction term. TEMPERpos=1 when TEMPER>0.

Source	SS	df	MS
Model	.007588746	3	.002529582
Residual	12.0520893	11,305	.001066085
Total	12.0596781	11,308	.001066473

Number of obs	=	11,309
F(3, 11305)	=	2.37
Prob > F	=	0.0683
R-squared	=	0.0006
Adj R-squared	=	0.0004
Root MSE	=	.03265

AR	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.SOE	.001242	.0013854	0.90	0.370	-.0014736	.0039575
1.TEMPERpos	.0020835	.0008088	2.58	0.010	.0004981	.0036688
SOE#TEMPERpos						
1 1	-.0019832	.0031723	-0.63	0.532	-.0082016	.0042351
_cons	-.0021322	.0003529	-6.04	0.000	-.0028239	-.0014405

Table 41: Regression models with lagged TEMPER

AR is the dependent variable. Regressors are described in chapter 3. SIZE is divided by 10million. In each subsequent regression, one control variable is added. SOE threshold 30% state ownership. TEMPER1 is the variable TEMPER lagged by one day.

	(1) AR	(2) AR	(3) AR	(4) AR
TEMPER1	-0.00886**	-0.00871**	-0.00907**	-0.00929**
	(-2.93)	(-2.90)	(-3.01)	(-3.07)
Size		0.000000201***	0.000000206***	0.000000206***
		(3.71)	(3.80)	(3.80)
Growth			-0.00000653	-0.00000696
			(-0.47)	(-0.50)
Leverage				-0.000000893
				(-0.89)
_cons	-0.00240***	-0.00288***	-0.00298***	-0.00286***
	(-6.11)	(-6.91)	(-7.14)	(-6.48)
N	11309	11246	11120	11015
R-sq	0.001	0.002	0.002	0.002
adj. R-sq	0.001	0.002	0.002	0.002

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 42: Regression model with interaction term (lagged TEMPER)

AR is the dependent variable. Regressors are described in chapter 3. SIZE is divided by 10million. In each subsequent regression, one control variable is added. SOE threshold 30% state ownership. TEMPER1 is the variable TEMPER lagged by one day. SOE#c.TEMPER1 is the interaction term.

Source	SS	df	MS			
				Number of obs	=	11,309
				F(3, 11305)	=	4.29
Model	.013719038	3	.004573013	Prob > F	=	0.0049
Residual	12.045959	11,305	.001065543	R-squared	=	0.0011
				Adj R-squared	=	0.0009
Total	12.0596781	11,308	.001066473	Root MSE	=	.03264

AR	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.SOE	.0027996	.0015933	1.76	0.079	-.0003235	.0059228
TEMPER1	-.0104078	.0031238	-3.33	0.001	-.0165309	-.0042847
SOE#c.TEMPER1						
1	.0238849	.012258	1.95	0.051	-.0001429	.0479128
_cons	-.0025789	.000406	-6.35	0.000	-.0033747	-.0017831